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Short Synopsis

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Title: Machine Intelligence based Detection and Classification of Human Physiology and Emotions

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ABSTRACT

Automated analysis of the physiological signals like ECG (electrocardiogram) and EEG (electroencephalogram) has become more extensive during the last three decades and is recognized as an effective clinical diagnostic tool in the physiological measurement field. Since most of the physiological signals including ECG and EEG are non-linear, non-stationary and non-Gaussian in nature, it is difficult to capture the respective large temporal and morphological variations for their automated analysis. Conventional physiological signal analysis tools such as linear and power spectrum estimation ignore random variations and the Fourier phase relationship among signal components. This can provide inaccurate analysis results. An effort shall be attempted to develop a more efficient and robust technique to analyze physiological signals using a fusion of time domain and frequency domain techniques. In this research, the physiological signals to be considered are ECG and EEG. The primary aim will be the analysis of ECG signals to develop an automated cardiac state detection and classification technique using machine intelligence tools like neural network classifier. The understanding obtained from primary aim shall be used to analyze EEG signals to interpret and classify correlated emotional states as this can lead to an effective way of implementing implicit man-machine interaction.

Key words: ECG (electrocardiogram), EEG (electroencephalogram), Cardiac states, Emotions, Machine intelligence, Time domain analysis, Frequency domain analysis, Neural Network classifier.

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1. Introduction

Computer aided analysis of the physiological signals like ECG (electrocardiogram) and EEG (electroencephalogram) is recognized as an effective clinical diagnostic tool in the physiological measurement field. Analysis of the noninvasive investigative parameter ECG is one of the most extensively studied fields to extract important information about clinical condition of the cardiac patients [25]. An ECG represents the electrical activity of heart recorded by skin electrodes placed at body surface points displaying the respective potential difference. The morphological (shape and size related) and temporal (durations/segments) parameters of the ECG waveform represents the overall functionality of the heart and thus reflects the state of cardiac health [3]. These parameter values have been standardized for normal human heart. Any deviation from these standardized values of ECG signal parameters due to variation in normal heart rhythm or change in ECG signal morphology represents a state of heart dysfunction, which can be detected by analysing the input ECG signal. Thus, ECG has become the most common and inexpensive clinical diagnostic tool to recognize human physiology and in turn provide subsequent therapy of the related cardiac diseases. Early detection and relative treatment of cardiac diseases are extremely crucial as it can prolong life and can prevent sudden death of the patient. The amount and nature of captured deviations in the recorded ECG from normal rhythm provide significant clinical information. For precise recognition of distinct cardiac abnormalities, it is important to capture and characterize these deviations in temporal and morphological parameters of ECG signal accurately. However, these corresponding subtle variations in ECG rhythm are difficult to analyse visually by naked human eye. Hence computer assisted analysis and classification of cardiac diseases can help cardiologists to monitor subject's cardiac health efficiently at early stages [6]. Automated analysis of ECG signals has been extensively used in the diagnosis of many cardiac diseases like ischemia, arrhythmias, and myocarditis, or heart rhythm disorders and for monitoring drug effects or pacemaker activity [12]. As each heartbeat consists of distinct cardiac events, represented by distinct time domain and frequency domain features in the ECG waveform [13]. Therefore, ECG beat classification for automated detection and classification of human cardiac states is very useful in healthcare technology, as it will help the doctor to diagnose and act faster in case of emergency conditions [7, 11].

Like analysis of ECG provides a lot of information about the human physiology through its patterns to diagnose cardiac disorders, similarly, the use of EEG has become more extensive for the development of Brain computer interfaces (BCI) to include areas like lie detection, stress and emotion measurement [38]. This sparked some interest in investigating whether an emotion could be recognized merely seeing the physiological response. People can hide their emotions from outside appearances such as altering pitch of speech and hiding facial expression. However, they cannot hide their emotions in physiological signal responses. This led to the development of emotion detection methods based on human physiological signals such as heart rate, skin conductance, cardiac activity, neural responses, [1] etc. Recent research reveals that monitoring of EEG signals has also been proven to be an effective and promising tool to analyze the human neural responses in context of emotion detection [16, 24]. Also, there is a huge demand as well as scope to make man-machine interface more affective and cognitive by developing algorithmic/software applications/solutions for new generation robotic devices. Artificial intelligence systems possessing these capabilities can have a huge range of real world applications in areas including control, psychiatry, medical field, lie detection, security services and telecommunications. Recognizing emotional states from physiological signals is an effective way of implementing implicit human-machine interaction [39]. Man-machine interface systems create a communication channel between the human and computer by acquiring, analyzing and classifying physiological activities under certain stimulations. Automated retrieval of emotional states from physiological signals like EEG is gaining noticeable attention nowadays since affective computing in the context of human neural responses can lead to the development of Brain computer interfaces. The designed BCIs can be further programmed towards the development of a neuro-scientific and medical tool that can progressively contribute to assist medically challenged people suffering from certain psychiatric/depression disorders. Hence, a need is there for the development of an efficient computer-aided method for automatic detection and classification of emotions based on human neural responses.

2. Literature Review

Literature presents several techniques for beat classification of ECG signal and emotion recognition from human brain activity. This section gives the most recent techniques implemented by the researchers for automated cardiac state recognition from human ECG signals followed by the methods used to extract emotions from human neural responses *i.e.*, EEG. Reddy *et al.* [34] in 2008, classified the cardiac arrhythmias using HRV (Heart rate variability) signal. They first extracted the ECG signal features by applying DWT (discrete wavelet transform) and then performed the statistical analysis to reduce variations in the extracted features of ECG which were ultimately used to train the feed forward neural network classifier for automated cardiac disorder classification. The proposed method achieved an overall accuracy of 90.56%. The major drawback of the algorithm was its complexity to calculate the statistical parameters used.

Jadhav *et al.* [18, 19] in 2010-2011, developed a Modular neural network (MNN) model based cardiac state classification system using static back propagation algorithm. The performance of configured MNN was evaluated by performing experiments using UCI Arrhythmia data set, containing 245 normal and 207 abnormal ECG records constituting a total of 452 ECG records. The classification accuracy achieved was 82.22%. This system classifies the cardiac disorders in only two broad categories of normal and abnormal classes. There was no information regarding the corresponding sub-category of the abnormal class.

Bulusu, S.C *et al.* [4] in 2011, firstly recognized and analyzed the ST-segment deviations and transient ST episodes in the ECG signal, which are of major significance in myocardial ischaemia diagnosis. Secondly, a classification algorithm was implemented using support vector machines (SVM) for recognition of major cardiac arrhythmias by extracting a morphological feature vector consisting of ST-segment information. They classified the input ECG signal into six classes; Normal, Ventricular, Fusion, Atrial, Left Bundle and Right Bundle Branch Block beats and achieved an overall classification accuracy of 96.35%. The limitation of this method was the use of large feature vector consisting of a total of 203 feature values. Although using a large number of features significantly enhances the classification performance but it increases the memory size requirement, learning time of the classifier while training and the test phase computations.

Kim *et al.* [22] in 2011, proposed an algorithm for cardiac arrhythmia classification, with an aim of reducing the differences in the ECG morphologies coming from personal characteristics of the subject by using dedicated wavelets adapted to individual subjects. The features were extracted by first applying a morphological filtering operation on input ECG signals. The filtered ECG signals in turn are subjected to continuous wavelet transform (CWT) operation with a dedicated wavelet for each subject. The whole extracted morphological feature set was compressed using principal component analysis (PCA) and linear discriminant analysis (LDA). An extreme learning machine based classifier was implemented to classify heart beats in five classes; normal, ventricular ectopic beat, supraventricular ectopic beat, the fusion beat and the unknown beat, with an accuracy of 97.94%. Although, the overall accuracy achieved was high but the use of dedicated CWT for each subject leads to the high computational load on the system, thus increased processing time.

Duttaa *et al.* [9] in 2011, developed an ECG beat classification algorithm. They used a cross-correlation based feature extraction tool to extract the frequency domain features of ECG signal. In turn, a robust cardiac arrhythmia detection algorithm was developed to classify three ECG beats *i.e.,* normal beats, Premature Ventricular Contraction (PVC) beats and other beats, using ANN classifier based on Learning Vector Quantization (LVQ) scheme. Their proposed scheme produced the overall high classification accuracy of 95.24% with a 30-feature vector length. The system was developed with an initial approach of maximum accuracy and early detection of associated cardiac arrhythmias. The limitation of the algorithm lies in the large feature vector that leads to computational burden and large storage requirement, and a limitation to classify heart beats in three classes only.

Karpagachelvi *et al.* [21] in 2011, published a comparative research to highlight the ECG beat classification capability of Extreme Learning Machine (ELM) classifier as compared to support vector machine (SVM). The performances of both the ELM classifier and SVM classifier are evaluated in terms of their respective classification accuracy. This has been implemented by selecting and detecting the best ECG beat discriminating features from the whole morphological and temporal feature set. They achieved the classification accuracy of 89.74%, while classifying the ECG beats into only two classes *i.e.,* normal and ventricular premature beat (VPB).

Rai *et al.* [35] in 2012, presented an ECG signal analysis technique using discrete wavelet transform for abnormality detection and classified ECG beats using Back Propagation Neural Network (BPNN) classifier. The feature vector consisting of wavelet coefficients based features and ECG signal morphological features, was used to classify the cardiac arrhythmias. Direct use of wavelet coefficients as inputs to the input layer neurons of the neural network may increase the neuron numbers which in turn can degrades network performance in terms of accuracy and processing time. Thus, they utilized the statistics (mean, standard deviation and variance) of the wavelet coefficients to reduce the extracted feature set dimensionality of length 64 (including 48 wavelet based features). The overall classification accuracy of 97.8% was achieved using BPNN classifier, but only to classify ECG beats into two classes; normal and abnormal.

Iftikhar *et al.* [17] in 2012, attempted to classify the heart beats into five important classes of premature atrial contraction/ premature ventricular contraction (PAC/PVC), left bundle branch block / right bundle branch block (LBBB/RBBB), paced beat and normal beat. They did the fusion of time domain (P, QRS, T wave amplitude and duration) and frequency domain (mean power frequency of the beat, power spectral density) features. This extracted feature set was used to train the Feed forward Back propagation neural network. The overall low classification accuracy of 78% was achieved for cardiac arrhythmia diagnosis.

Yun-Chi Yeh [45] in 2012, proposed an efficient and reliable heart beat classification algorithm using dimensionality reduction method of Principal Component Analysis (PCA) and Fuzzy Logic. The feature vector used consists of P-QRS-T wave features (Morphological and temporal ECG features) and the qualitative features of ECG signal. The study used Principal Component Analysis for selection of qualitative features, and classification of the corresponding heartbeat was carried out by fuzzy logic. Thus, a fuzzy logic based algorithm was developed to classify the heart beats into six classes *i.e.*, normal (NORM), right bundle branch block (RBBB), left bundle branch block (LBBB), ventricular premature contractions (VPC), atrial premature contractions (APC), and paced beat (PB) with classification accuracy of 94.03%.

Apart from these linear feature extraction techniques which provide a large feature vector and also suppress the phase information between the frequency components of the ECG signal, higher order spectra (HOS) dependent techniques have also been explored by the

researchers to classify the cardiac disorders more efficiently. Earlier Khadra *et al.* in 2005, utilized the quantified bispectral features of HOS analysis technique for classification of cardiac arrhythmias. Atrial and ventricular tachy arrhythmias are detected by estimating the bispectrum of input ECG signal using an autoregressive model. Differences in obtained parameter values and bicoherency values indicate the different cardiac states.

Further Karimfarid *et al.* [23] in 2007, 2011, developed an efficient morphological cardiac arrhythmia detection and classification system using the second (autocorrelation), third (skewness) and fourth (kurtosis) order cumulants of the input ECG signal. These cumulants can effectively reduce the effect of Gaussian noise as well as capture and suppress the random morphological variations of ECG signals (non-stationary in nature). Instead of using large samples of cumulants directly as a feature vector, the technique first performs Hermitian model on the cumulants to obtain a smaller length feature set to classify the cardiac arrhythmias into five classes (normal, atrial premature beat, ventricular premature beat, right and left bundle branch block beats) using 1-Nearest Neighbourhood classifier and obtained a sensitivity and specificity of 98.59% and 99.67% respectively.

Chua *et al.* [7] in 2008-2009, developed an algorithm for diagnosis of cardiac disorders by applying higher order spectra (HOS) technique on heart rate variability (HRV) signal. They used HOS (a non-linear technique) to analyze and classify non-linear ECG signals, by utilizing their bispectrum invariant features and phase entropies. This work investigated the ability of HOS particularly bispectrum features of HRV data to classify cardiac states into eight classes and obtained an accuracy of 83%.

Martis *et al*. [26, 27] in 2013, developed an algorithm for cardiac state recognition by applying higher order spectra (HOS) to input ECG signals. They used third order spectra (bi-spectrum) of the ECG signal to capture the statistical features beyond mean and standard deviation. Further the obtained feature set was reduced in dimensions by subjecting it to PCA (Principal Component Analysis) and the reduced feature set was used to configure a four layered feed-forward neural network for automated cardiac arrhythmia classification. They obtained high accuracy of 93.48%, sensitivity of 99.27% and specificity of 98.31% respectively, while classifying cardiac disorders in five classes; normal, left and right bundle branch block, ventricular premature contraction and atrial premature contraction. The resultant high accuracy, sensitivity and specificity of the developed bispectrum based classification

algorithm justify the clinical significance of higher order spectral analysis (third order) in the analysis and thus classification of life threatening heart disorders.

Apart from the above techniques, many other algorithms have been proposed and developed in the literature for automated analysis and classification of human cardiac states using; ECG morphology [8], artificial neural networks [10], [36], support vector machines [30], fuzzy neural networks [31], mixture of experts approach [14], autoregressive modeling [41], time and frequency domain analysis in fusion with several knowledge-based [43], and rule-based systems [44]. The above latest findings reveal that the developed ECG beat classification systems have addressed a wide variety of clinical and technical issues but their performance is still lacking in terms of the size of feature vector extracted from each ECG beat and thus, in turn complexity and response time of the system. Considering the above facts an effort shall be attempted to develop an efficient and accurate cardiac state detection and classification technique.

Algorithm developed to categorize ECG signals would be further utilized to understand EEG signals in context with human emotions. This section reviews the advances in emotion recognition using EEG since emotion recognition using specific features of EEG is less explored than other physiological responses. Thus the current progress through literature will be accessed in order to find the relationship between emotions and the unique patterns of EEG waveform.

Monitoring and analyzing the human neural responses through EEG has proven to be an effective method of emotion detection. Sim *et al.* [24] in 2009, detected the human emotions from EEG signal by dividing the corresponding EEG into five EEG sub-bands by estimating the respective power spectrum density (PSD). Then these sub-bands were compared with the standard EEG sub-bands to measure the emotions using Bayesian network. While evaluating results, different probability values have been obtained for different categories of emotions, while a similarity trend has been observed in respective probability values of anger and sadness emotions. Further, the linear technique of PSD was utilized to extract the emotions from non-linear EEG signal.

Schaaff *et al.* [39] in 2009, developed an emotion recognition system by extracting the and fusing together time domain and frequency domain features of EEG signal. They classified the emotions into three categories with an average low recognition rate of 43.11% using SVM.

Another research investigates the application of optimization techniques including different sizes of sliding windows, normalization approaches, filtering methods and dimensionality reduction algorithms on time domain and frequency domain features of EEG signal to distinguish pleasant, neutral, and unpleasant emotional states using support vector machines (SVM) [40].

Yaacob *et al.* [46] in 2010, utilized lifting based discrete wavelet transforms (DWT) in fusion with spatial filtering to extract emotion related features of EEG in order to classify happiness, sadness, disgust, and fear emotions using Fuzzy C-Means clustering algorithms. DWT based techniques are not so favorite due to large feature set.

Hosseni *et al.* [15, 16] in 2010, developed an algorithm to detect emotional stress from human EEG signals by applying higher order spectra (HOS) technique. They detected and classified the emotional stress in two categories (calm neutral and negatively excited) by configuring an LDA classifier. The classification accuracy of 82.3% was achieved by employing the HOS technique (bi-spectrum) to input EEG signals for their analysis and feature extraction for automated emotion detection and classification.

Petrantonakis *et al.* [32]n in 2010, presented a technique to detect and classify the emotions by applying higher order crossings analysis technique to human EEG signals and achieved higher classification rates to classify the emotions into six categories [33].

Mikhail *et al.* [28] in 2013, classified the emotions in four classes by extracting the features from the alpha band of the EEG signal after the application of Fast Fourier Transform. Emotions were classified into four categories of anger, fear, joy and sadness using SVM with an accuracy of 53%, 58%, 51% and 61% respectively.

The above latest findings indicate that emotional state is reflected in human physiological signals. Literature also reveals that the higher order spectra (HOS), being a non-linear technique can be a high performance, reliable and robust method in investigating the behavior of human heart (ECG) and brain (EEG) while detecting cardiac arrhythmias and human emotions. Along with this artificial neural network (ANN) proves to be a significant mathematical tool in the medical field for the physiological signal mapping. Further, feature extraction algorithm to extract the ECG and EEG signal features must be highly accurate and fast [20]. This will lead to an efficient classification of cardiac disorders and the human emotions using physiological signals ECG and EEG, respectively.

3. Description of Topic

Electrocardiogram being a non-invasive technique is an established parameter used for diagnosis of cardiac disorders. It provides significant clinical information regarding the functionality of the heart and thus cardiac system. The above detailed literature reports reveal that the use of physiological signals like EEG has also been gaining a great popularity in the detection and classification of the different emotional states. Since most of the physiological signals including ECG and EEG are non-linear, non-stationary and non-Gaussian in nature, it is difficult to capture the respective large temporal and morphological variations for their automated analysis [2]. Literature reports reveal that several algorithms have been developed for the automatic analysis, detection and classification of human cardiac disorders and emotional states. Earlier, linear methods like correlation and the power spectrum were used in physiological signal processing [6]. The limitation of these linear methods lies in the fact that the phase relationships between the frequency components of the signal gets suppressed [6, 23]. This can provide inaccurate analysis results. However, the variations in the morphological and temporal parameters of these signals corresponding to the particular cardiac disease or emotion can be characterized efficiently using non-linear higher order spectra (HOS) technique, as HOS are less sensitive to the random variations in the morphology of physiological signals like ECG and EEG [31]. Therefore, physiological signal analysis using HOS can be more advantageous with higher order spectra as compared to correlation and power spectrum estimation [6, 27]. This leads to more efficient detection and classification of cardiac arrhythmias and human emotions from physiological signals [23].

In order to obtain the higher order spectra of a signal, the principles of power spectrum estimation and correlation functions are extended to third and fourth order. The second, third and the fourth order spectra of the signal is known as the power spectrum (variance), bispectrum (skewness) and the trispectrum (kurtosis), respectively [6, 27]. The trispectrum contains more shapes than the bispectrum and its represents kurtosis over frequency, thus, provides more information about the parameters of corresponding physiological signal [5]. Thus, trispectrum can be a more efficient and powerful tool for automated analysis of physiological signals like ECG and EEG. Many studies in the literature have shown correlation between morphology of various physiological signals and their HOS analysis. Therefore,

effectiveness of this correlation shall be explored in detail to accurately extract the morphological and temporal features of input ECG signals for efficient cardiac state assessment. The understanding obtained shall be used to analyze human neural responses (EEG) to interpret and retrieve correlated human emotions.

A typical ECG cycle (one heartbeat) is the graphical representation of heart's electrical activity and is constituting of P-QRS-T complex [38]. The ECG signal is a very low amplitude signal of about 10 μV with frequency range lying between 0.5Hz to 100Hz [34]. Each ECG signal record is inspected for both temporal and morphological parameters including shape/slope, duration of associated intervals and segments of P wave, QRS complex, and T wave components present. Any change in these parameters reflects the presence of an abnormality[34]. Similarly, an EEG signal represents electrical activity of the brain. A typical EEG signal has amplitude of 10 to 100 microvolt and the frequency of EEG signal lies in the range of 1 to 100Hz. EEG signals are characterized by five frequency sub-bands, defined as; delta band (1-4 Hz), theta band (4-8 Hz), alpha band (8-13 Hz), beta1 band (13-18 Hz), beta2 band (18-30 Hz) and gamma band (>30 Hz) [42]. These EEG signal frequency bands are associated with the neural activity and tend to change under different circumstances [16]. Thus, by extracting these features and analyzing them, it is possible to get the right perception about the correlated emotional state for developing a intelligent man machine interface using EEG.

4. Objectives of Research

Problem statement formulation:

Computer assisted automatic analysis and classification of basic human physiological parameters like ECG and EEG with higher accuracy and reduced complexity is the need of the hour. Accurate interpretation of ECG signal would assist a physician in diagnosing and treating cardiac patients at early stages and understanding of EEG data shall serve as a basis for developing an intelligent and affective man-machine interface. Recognizing emotional states from human physiological signals is an effective way of implementing implicit human-robot interaction using affective computing. Hence, a need is there for the development of an efficient computer-aided method for automatic detection and classification of cardiac states from ECG and human emotions based on EEG.

Objectives of the research shall be:

- To develop an ECG beat classification technique to detect different cardiac states using hybrid features (temporal features and higher order statistical features) of ECG and artificial intelligence tools like neural network classifier.
- To develop an algorithm for the identification of P-QRS-T complexes in ECG signal to establish an appropriate and relevant set of QRS dependent and higher order spectral dependent features to detect various cardiac disorders from input ECG signal records extracted from the MIT-BIH arrhythmia database of Physiobank ATM.
- To configure and train a classifier by reducing the error rates, training time and thus increasing the cardiac state classification accuracy using MATLAB.
- To test the developed algorithm on different ECG signal records available at MIT-BIH arrhythmia database for its robustness in detection and classification of various cardiac disorders effectively and efficiently.
- To further develop an efficient emotion detection and classification technique, based on compact and efficient feature set of EEG.
- To construct emotion specific physiological signal dataset from healthy volunteers by external stimulation, to make them experience the selected emotional state and simultaneously acquiring the associated neural responses in terms of EEG.

- To perform primary signal analysis and processing of real time acquired EEG using MATLAB based advanced brain mapping toolboxes.
- To develop an algorithm to establish an appropriate and relevant feature set of EEG signal to detect the associated human emotions. The efforts shall also be directed towards investigating the various combinations of feature sets of attained EEG signals to increase the classification rate to interpret human mental states in order to enrich human-computer interface.

5. Methodology to be adopted

Methodology to be adopted for automatic detection and classification of human physiology and emotions shall consist of two phases. In phase one ECG beat classification for cardiac state analysis shall be done using work flow graph shown in Fig. 1. The proposed technique of ECG beat classification for cardiac state recognition will be comprised of three steps *viz.*, preprocessing of ECG signals, feature extraction from preprocessed signals and classification of correlated cardiac states.

Preprocessing of ECG signals: Dataset for cardiac state detection will be loaded from the MIT-BIH arrhythmia database of Physiobank ATM [29] to MATLAB workspace. The preprocessing step will be done to make the signal suitable for feature extraction. The role of preprocessing is to segment the required pattern from the background. In this step, noise filtering, smoothing and normalization will be done.

Feature extraction from preprocessed ECG signals: In the feature extraction stage, hybrid feature vector consisting of temporal features and higher order spectral dependent features will be extracted from the preprocessed ECG signals, to obtain the effective classification of the cardiac arrhythmias from ECG. A good feature extraction methodology can accurately classify cardiac abnormalities. The extracted feature set shall serve as an input to train and test a classifier.

Classification of correlated cardiac states: The preprocessed ECG signals shall be mapped to the extracted feature set to be utilized by the classifier to determine the corresponding cardiac defect. This feature set consisting of a combination of complicated temporal characteristics and higher order statistics should efficiently characterize the variations in the input ECG signals for accurate detection and classification of human physiology in terms of their associated cardiac state. The extracted hybrid feature vector will be applied to the decision support systems like neural network classifier as training and testing data to classify the cardiac arrhythmias in their corresponding class. The neural network analysis toolbox shall be utilized to train and test the network for cardiac state classification.

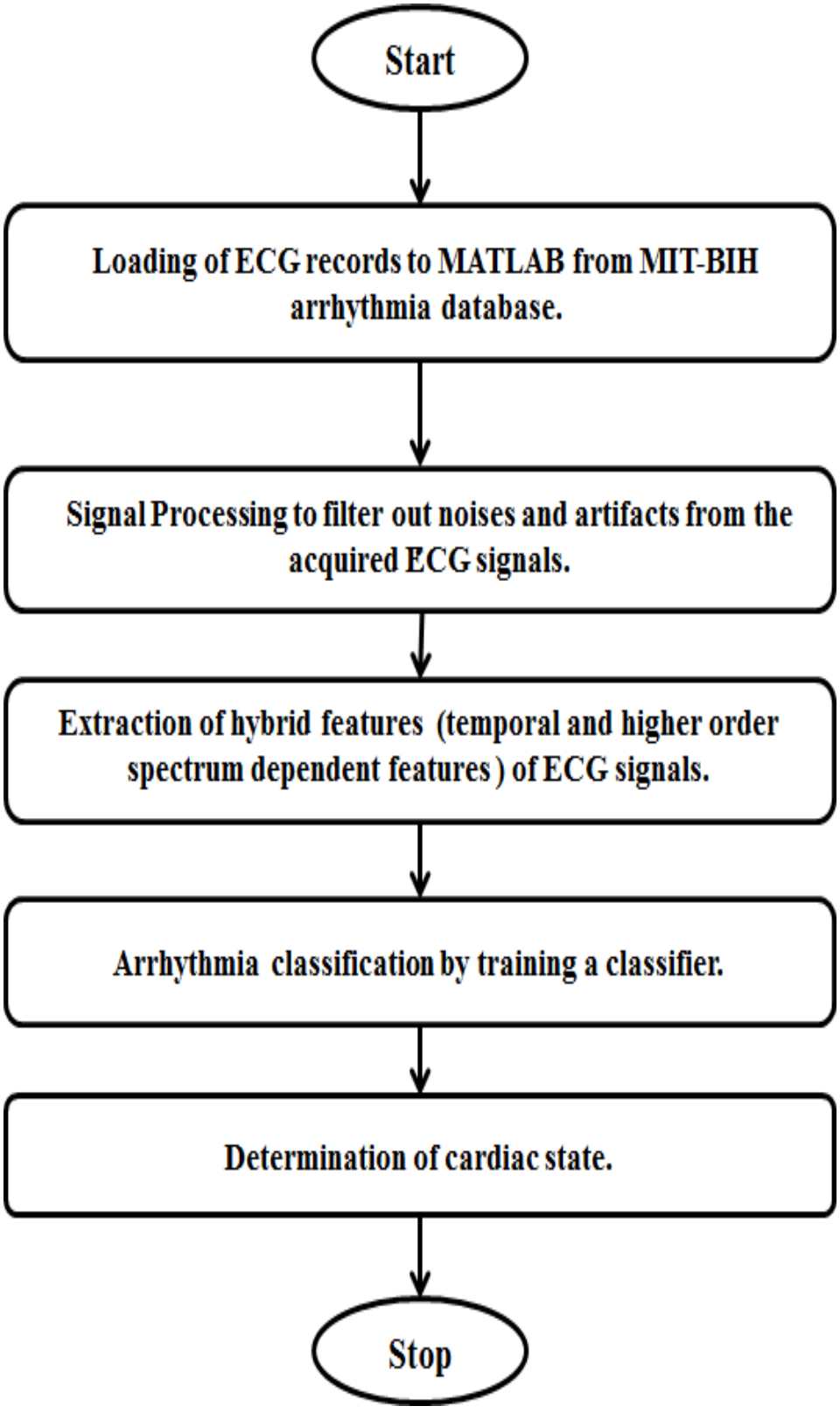

Start
Loading of ECG records to MATLAB from MIT-BIH arrhythmia database.
Signal Processing to filter out noises and artifacts from the acquired ECG signals.
Extraction of hybrid features (temporal and higher order spectrum dependent features) of ECG signals.
Arrhythmia classification by training a classifier.
Determination of cardiac state.
Stop

Fig. 1: Work flow graph of cardiac state detection and classification system using ECG.

In second phase, real time EEG data shall be acquired and processed for detection and analysis of correlated emotional state using work flow graph shown in Fig. 2. The subjects will be externally stimulated using some effective mode, to make them experience the selected emotional state. The associated neural responses in terms of EEG signal shall be acquired. The primary signal analysis and processing of real time acquired EEG shall be performed using MATLAB based advanced brain mapping toolboxes like EEGlab. This shall be followed by the development of EEG signal classification technique for human emotional state recognition that will be comprised of three steps *viz.*, preprocessing of EEG signals, feature extraction from preprocessed signals and classification of correlated emotional states.

Acquisition and preprocessing of EEG signals: EEG signal dataset for emotional state detection will be acquired using EEG acquisition device and loaded to MATLAB workspace. The emotion based EEG database shall be created in response to external audio/video stimuli. The preprocessing step will be done to make the signal suitable for feature extraction.

Feature extraction from acquired EEG signals: In the feature extraction stage, a set of time and frequency domain features of EEG signal will be extracted from the preprocessed EEG signals, to effectively recognize associated human emotions from EEG. A good feature extraction methodology can accurately classify distinct human emotional states. The extracted feature set shall serve as an input to train and test a classifier.

Classification of correlated emotional states: The preprocessed EEG signals shall be mapped to the extracted feature set to be utilized by the classifier to determine the corresponding emotional state. This feature set consisting of time and frequency domain features of EEG should efficiently characterize the associated changes in the input signals for accurate human emotion classification. The extracted hybrid feature vector will be applied to the decision support systems as training and testing data to classify the human emotions in their corresponding class.

While developing automatic emotion detection and classification system, the neural responses through EEG signals shall be analyzed and monitored in order to obtain the better classification results.

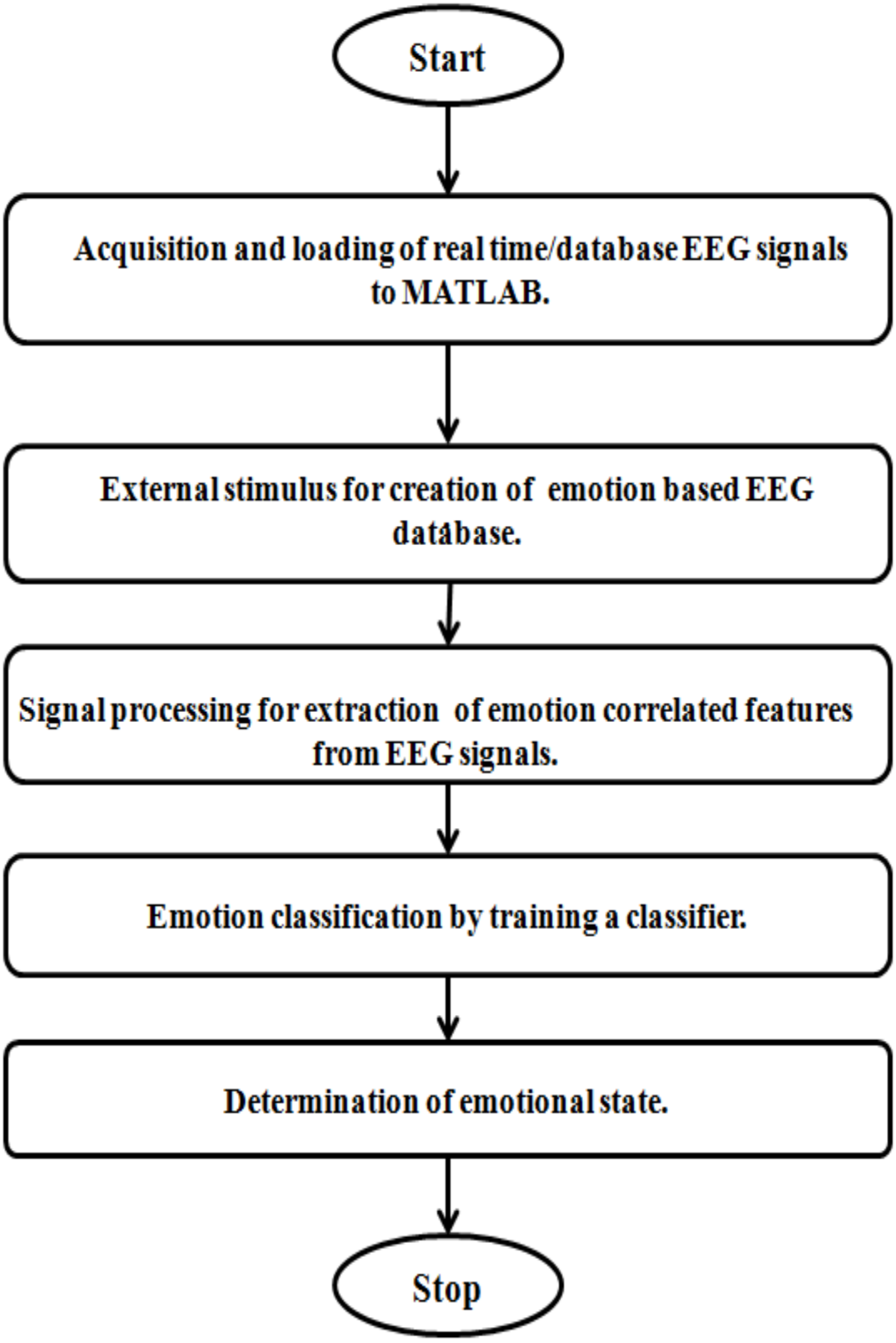

Start
Acquisition and loading of real time/database EEG signals to MATLAB.
External stimulus for creation of emotion based EEG database.
Signal processing for extraction of emotion correlated features from EEG signals.
Emotion classification by training a classifier.
Determination of emotional state.
Stop

Fig. 2: Work flow graph of human emotion detection and classification system using EEG.

Finally, the performance and efficiency of the proposed method for automated detection and classification of human physiology using ECG signals and human emotions using EEG signals will be evaluated in terms of overall accuracy and the error rate [4, 18].

1. Accuracy: Accuracy is defined as the ratio of the number of correctly classified cases (TP + TN), divided by the total number of cases (TP + TN + FP + FN) [18].

$$Accuracy\ (Acc) = \frac{TP+TN}{TP+TN+FP+FN}$$

2. Error rate: Error rate can be calculated as

$$Error\ rate\ (E) = 1 - Acc$$

where, TP = Number of True Positive beats/ emotions detected

FP = Number of False Positive beats/ emotions detected

FN = Number of False Negative beats/ emotions detected

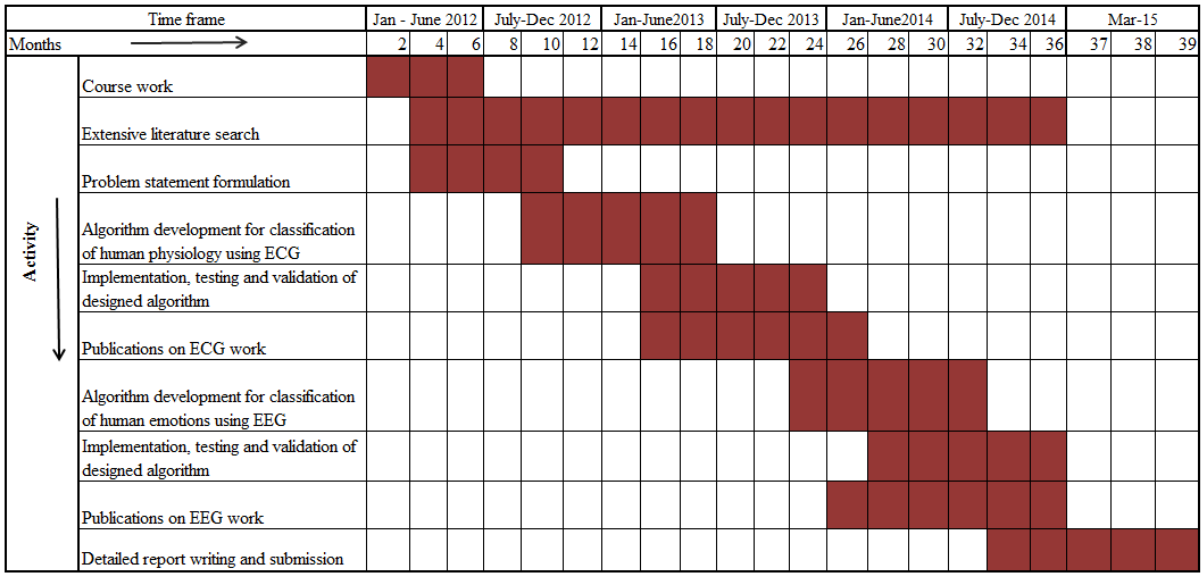
TN = Number of True Negative beats/ emotions detected

An ideal test will possess a high overall accuracy and low error rate, for classification of the cardiac arrhythmias using ECG and human emotions using EEG signals.

6. Proposed/expected outcome of the research

1. First outcome of this research will an efficient computer-automated ECG beat classification technique to detect different cardiac arrhythmias using hybrid features (temporal and higher order statistical features) and artificial intelligence tools like ANN/ SVM which would assist effective clinical diagnosis of heart disease. The beat classification technique developed shall be able to classify the category of abnormal or normal ECG signal.
2. Secondly, the system shall give efficient human emotion detection and classification technique, using hybrid linear and nonlinear features of real time/database EEG data to enrich human-computer interface.

7. Proposed Time Frame (Gantt Chart)


Time frame
Jan - June 2012
July-Dec 2012
Jan-June2013
July-Dec 2013
Jan-June2014
July-Dec 2014
Mar-15
Months
2 4 6 8 10 12 14 16 18 20 22 24 26 28 30 32 34 36 37 38 39
Activity
Course work
Extensive literature search
Problem statement formulation
Algorithm development for classification of human physiology using ECG
Implementation, testing and validation of designed algorithm
Publications on ECG work
Algorithm development for classification of human emotions using EEG
Implementation, testing and validation of designed algorithm
Publications on EEG work
Detailed report writing and submission

References:

[1] Agrafioti F, Hatzinakos D, Anderson A.K, "ECG Pattern Analysis for Emotion Detection", IEEE Transactions on Affective Computing, 2012. **3**(1): p. 102-115.

[2] Balli T, Palaniappan R, "Classification of biological signals using linear and nonlinear features", Physiological Measurement, 2010. 31: p. 1-18.

[3] Braunwald, E, "Heart Disease: A Textbook of Cardiovascular Medicine", Fifth ed. 1997, Philadelphia: W.B. Saunders Co, 108.

[4] Bulusu S.C, Faezipour M, Nourani M, Tamil L.S, Banerjee S, "Transient ST-segment episode detection for ECG beat classification", IEEE/NIH Life Science Systems and Applications Workshop (LiSSA). 2011: p. 12-124.

[5] Chandran V, Elgar S, "Statistics of Tricoherence", IEEE transactions on signal processing, 1994. 42(12): p. 3430-3440.

[6] Chua K.C, Chandran V, Acharya R, "Application of higher order statistics/spectra in biomedical signals - a review", Journal of Medical Engineering and Physics, 2010. **32**(7): p. 679-689.

[7] Chua K.C, Chandran V, Acharya R, Lim C.M, "Cardiac state diagnosis using higher order spectra of heart rate variability", Journal of Medical Engineering & Technology, 2008. **32**(2): p. 145-155.

[8] Chazal P, O'Dwyer D, Reilly R.B, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features", IEEE Trans on Biomed Engg, 2004. **51**(7): p. 1196-206.

[9] Duttaa S, Chatterjee A, Munshi S, "Identification of ECG beats from cross-spectrum information aided learning vector quantization", Measurement, 2011. **44**(10): p. 2020-2027.

[10] Dokur Z, Olmez T, "ECG beat classification by a hybrid neural network", Comput Meth Prog Biomed, 2001. **66**: p. 167-181.

[11] Exarchos T.P, Tsipouras M.G, Michalis L.K, "A methodology for the automated creation of fuzzy expert systems for ischaemic and arrhythmic beat classification based on a set of rules obtained by a decision tree", Artif Intell Med, 2007. **40**(3): p. 187-200.

[12] Filho E.B, Rodrigues N.M, "On ECG signal compression with 1-D multiscale recurrent patterns allied to preprocessing techniques", IEEE Trans Biomed Eng, 2009. **56**(3): p. 896-900.

[13] Finlay D.D, Nugent C.D, "Mining for diagnostic information in body surface potential maps: a comparison of feature selection techniques", Biomed Eng Online, 2005. **4**: p. 51.

[14] Hu Y.H, Palreddy S, Tompkins W.J, "A patient-adaptable ECG beat classifier using a mixture of experts approach", IEEE Trans Biomed Eng, 1997. **44**(9): p. 891-900.

[15] Hosseini S.A, Khalilzadeh M.A, Naghibi-Sistani M.B, Niazmand V, "Higher Order Spectra Analysis of EEG Signals in Emotional Stress States", ITCS '10 Proceedings of the 2010 Second International Conference on Information Technology and Computer Science 2010. IEEE Computer Society Washington, DC, USA ©2010: p. 60-63.

[16] Hosseini S.A, Classification of Brain Activity in Emotional States Using HOS Analysis. International Journal of Image, Graphics and Signal Processing 2012. 4(1): p. 21-27.

[17] Iftikhar F, Shams A, Dilawari A, "Rhythm Disorders-Heart Beat Classification of an Electrocardiogram Signal", International Journal of Computer Applications, 2012. **39**(11): p. 38-44.

[18] Jadhav S.M, Nalbalwar S.L, Ghatol A.A, "Modular Neural Network Based Arrhythmia Classification System Using ECG Signal Data", International Journal of Information Technology and Knowledge Management, 2011. **4**(1): p. 205-209.

[19] Jadhav S.M, Nalbalwar S.L, Ghatol A.A,, "Artificial Neural Network based cardiac arrhythmia classification using ECG signal data", IEEE, International Conference On Electronics and Information Engineering (ICEIE). 2010,Kyoto : p. 1-6.

[20] Karpagachelvi S.A, Sivakumar M, "ECG Feature extraction techniques- A survey approach", International Journal of Computer Science and Information security, 2010. **8**(1): p. 76-80.

[21] Karpagachelvi S.A, Sivakumar M., "Classification of ECG Signals Using Extreme Learning Machine", Computer and Information Science, 2011. **4**(1): p. 42-52.

[22] Kim J.M, Min S.D, Lee M, "An arrhythmia classification algorithm using a dedicated wavelet adapted to different subjects", Biomed Eng Online, 2011. **10**(1).

[23] Karimifard S.A, Ahmadian A, "A Morphological Heart Arrhythmia Classification Using Hermitian Model of Higher-Order Statistics", Proceedings of the 29th Annual International Conference of the IEEE -EMBS. 2007. Lyon, France: p. 3132-3135.

[24] Ko K.E, Yang H.C, Sim K.B, "Emotion recognition using EEG signals with relative power values and Bayesian network", International Journal of Control, Automation and Systems 2009. 7(5): p. 865-870.

[25] Lannoy G, Verleysen M, "A Supervised Learning Appoach based on the Continuous Wavelet Transform for R spike Detection in ECG", Proceedings of the First International Conference on Biomedical Electronics and Devices, Biosignals. 2008, Madeira, Potugal: p. 140-145.

[26] Martis R.J, Acharya U.R, Chakraborty C, "Cardiac decision making using higher order spectra", Biomedical Signal Processing and Control, 2013. **8**(2): p. 193-203.

[27] Martis R.J, Acharya U.R, Chakraborty C, "Application of higher order cumulants to ECG signals for the cardiac health diagnosis", Conf Proc IEEE Eng Med Biol Soc, 2011: p. 1697-700.

[28] Mikhail M, Ayat K.E, "Using minimal number of electrodes for emotion detection using brain signals produced from a new elicitation technique", Int. J. Autonomous and Adaptive Communications Systems, 2013. 6(1): p. 80-97.

[29] MIT-BIH Database distribution, Massachusetts Institute of Technology, 77 Massachusetts Avenue, Cambridge, MA 02139, 1998. http://www.physionet.org/physiobank/database/mitdb/.

[30] Osowski S, Hoai L.T, Markiewicz T, "Support vector machine-based expert system for reliable heartbeat recognition", IEEE Trans Biomed Eng, 2004. **51**(4): p. 582-589.

[31] Osowski S, Linh T.H, "ECG beat recognition using fuzzy hybrid neural network", IEEE Transactions on Biomedical Engg, 2001. **48(11)**: p. 1265-1271.

[32] Petrantonakis P.C, Hadjileontiadis L.J, "Emotion Recognition from Brain Signals Using Hybrid Adaptive Filtering and Higher Order Crossings Analysis", IEEE Transactions on Affective Computing, 2010. 1(2): p. 81-97.

[33] Petrantonakis P.C, Hadjileontiadis L.J, "EEG-based emotion recognition using hybrid filtering and higher order crossings", 3rd International Conference on Affective

Computing and Intelligent Interaction (ACII) and Workshops: IEEE, Amsterdam, 2009:p. 1-6.

[34] Reddy V.C, Anuradha B, "ANN for Classification of Cardiac Arrhythmias", ARPN Journal of Engineering and Applied Sciences, 2008. **3**(3): p. 1-6.

[35] Rai H.M, Trivedi A, "Classification of ECG Waveforms for Abnormalities Detection using DWT and Back Propagation Algorithm", International Journal of Advanced Research in Computer Engineering & Technology, 2012. **1**(4): p. 517-520.

[36] Rao A, Bhat P.S, Iyengar S, Dua S, "Classification of heart rate data using artificial neural network and fuzzy equivalence relation", Pat Recogn, 2003. **36**: p. 61-68.

[37] Renumadhavi C, Ananth A.G, Srinivasan N, "A New Approach For Evaluating SNR Of ECG Signals And Its Implementation", Proceedings of the 6th WSEAS International Conference on Simulation, Modelling and Optimization, Lisbon, Portugal, 2006: p. 202-205.

[38] Rainville P, Bechara A, Naqui N, "Basic emotions are associated with distinct patterns of cardiorespiratory activity", International Journal of Psychophysiology, 2006. **61**(1): p. 5-18.

[39] Schaaff K, Schultz T, " Towards an EEG-based Emotion Recognizer for Humanoid Robots ", in The 18th IEEE International Symposium on Robot and Human Interactive Communication, Toyama, Japan. 2009: p. 792-796.

[40] Schaaff K. and Schultz T., "Towards Emotion Recognition from Electroencephalographic Signals", Proc. Of 3rd International Conference on Affective Computing and Intelligent Interaction (ACII) and Workshops, pp. 1-6, 2009.

[41] Srinivasan N, Krishnan S.M, "Cardiac arrhythmia classification using autoregressive modeling", Biomed Eng OnLine, 2002. **1**(5).

[42] Subha D.P, Joseph P.K, Acharya R, Lim C.M, "EEG Signal Analysis: A Survey", Journal of Medical Systems, 2010. 34(2): p. 195-212

[43] Tsipouras M.G, Sideris D, "Arrhythmia classification using the RR-interval duration signal", Proceedings of the computers in cardiology, IEEE. 2002: p. 485-488.

[44] Tsipouras M.G, Fotiadis D.I, Sideris D, "An arrhythmia classification system based on the RR-interval signal", Artif Intell Med, 2005. **33**(3): p. 237-50.

[45] Yeh Y.C, “An Analysis of ECG for Determining Heartbeat Case by Using the Principal Component Analysis and Fuzzy Logic”, International Journal of Fuzzy Systems, 2012. **14**(2): p. 233-241.

[46] Yaacob S., Murugappan M. and Nagarajan R., “Combining spatial filtering and wavelet transform for classifying human emotions using EEG signals”, J. Med. Biol. Eng., vol. 31(1), pp.45-51, 2010.